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Bio-economic evaluation of cropping systems for saline coastal Bangladesh: I. Biophysical simulation in historical and future environments

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ABSTRACT

Climate change, increased climate variability, extreme weather events, and increasing salinization pose a serious challenge to the sustainability of crop production in coastal Bangladesh. This study assessed yield performance of rice and non-rice crops under farmers' current practices across five climate and three salinity scenarios in the south-western coastal zone. Representative village case studies in Khulna District were used to obtain data on current cropping practices and yields. A validated biophysical crop simulation model (APSIM) was used to simulate performance of crops within 10 cropping systems, representing both existing and potential future cropping patterns. The salinity impact on rice crops was simulated directly using an improved APSIM model, capable of simulating both soil salinity dynamics and the resulting rice crop response. The salinity impact on maize, wheat and sunflower was assessed by developing crop salinity response functions and applying these post-simulation to the crop yields simulated in the absence of salinity. The future performance of some existing crops, namely, watermelon, and pumpkin were extrapolated from data available in the literature and expert knowledge. Climate change is projected to have both positive and negative impacts on crop yields but growing salinity is projected to have substantial negative effects. Allowing for uncertainties inherent in the modelling process, the results indicate that loss of crop production would be negligible under projected 2030 conditions for climate and salinity, even with farmers' current practices. Under 2060 conditions, the adverse impacts on wet-season rice, dry-season rice, and wheat remained negligible, while sunflower experienced notable yield decline. However, the effects of 2060 conditions on early wet season rice and dry-season maize were positive. Climate change in itself does not pose a major risk to crop production and aquaculture in south-west coastal Bangladesh over the next 15–45 years but increasingly salinity will have an unambiguously negative influence.

1. Introduction

The coastal zone of Bangladesh covers about 32% (47,551 km^2) of the total area of Bangladesh (Fig. 1) (BBS, 2016). In common with the other major river deltas and food baskets of South and South East Asia, such as the Irrawaddy, Chao Praya, and Mekong systems, climate change and salinization are the two biggest environmental challenges to sustainable agriculture in the coastal zone of Bangladesh (Wassmann et al., 2009; Mainuddin et al., 2013; Brammer, 2014; Dasgupta et al., 2015; Kabir et al., 2016). Though obviously interrelated, they are partly independent phenomena; even in the absence of further climate change, salinity may go on increasing. Of the total area of cultivated land in the coastal region (1,689,000 ha), about 63% (1,056,000 ha) is affected by various degrees of salinity (SRDI, 2012). From 1973 to 2009, 223,000 ha of non-saline land became affected by salinity (SRDI, 2012). Salinity intrusion will be further elevated during the current century due to sea-level rise (Agrawala et al., 2003; WB, 2013). The coastal systems of low-lying developing countries like Bangladesh are increasingly expected to face adverse impacts including damage to infrastructure, submergence, flooding, and erosion due to sea-level rise in the 21st century and beyond (IPCC, 2014a). The sea-level rise at the Bangladesh coast is likely to be about 0.1 m by 2020 and 0.25 m by 2050 compared with the base year (2000), resulting in inundation of 4% of agricultural and non-agricultural land by 2050 (Agrawala et al., 2003). The livelihoods of about 38.5 M coastal dwellers in Bangladesh – whether engaged in cropping, livestock rearing, aquaculture, or non-

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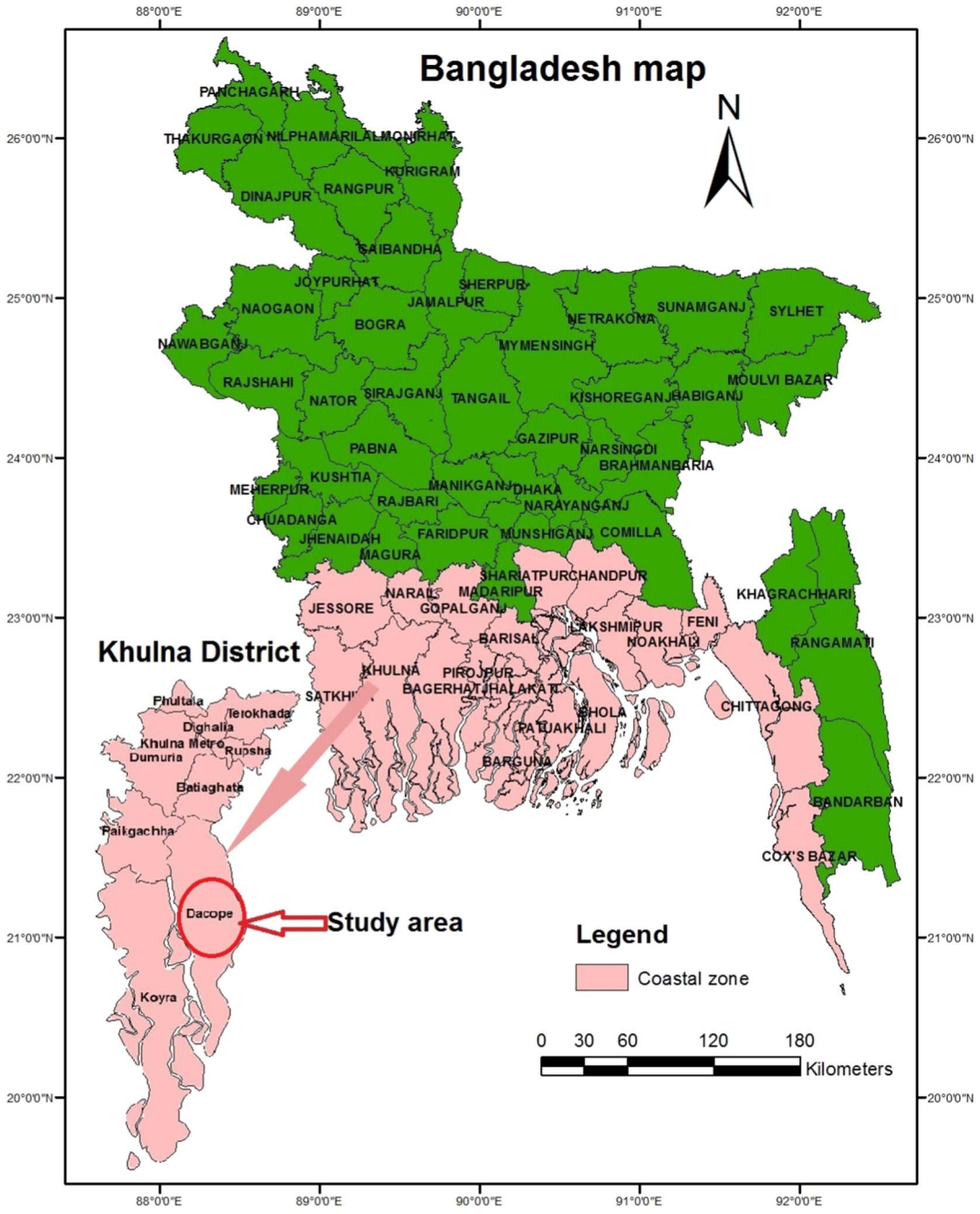

Fig. 1. Bangladesh and Khulna District map (study location is circled), prepared by Agricultural Statistics Division, Bangladesh Rice Research Institute.

farm activities – will be seriously affected by these projected changes in climate and environment (Agrawala et al., 2003; BBS, 2011; WB, 2013; Habiba et al., 2014).

A number of studies have been undertaken on the impacts of climate change on agriculture in Bangladesh. Previous studies have applied cropping systems models such as DSSAT (Yu et al., 2010; Alam and Ahmed, 2010; Basak et al., 2010; Hussain, 2011; Ruane et al., 2013), CROPWAT (Roy et al., 2009; Lázár et al., 2015), ORYZA (Mohandass et al., 1995; Karim et al., 2012; Timsina et al., 2016), CERES (Faisal and Parveen, 2004; Ruane et al., 2013), DCGE (Thurlow et al., 2012), regression models (Sarker et al., 2012), systematic review and meta-analysis (Wassmann et al., 2009; Challinor et al., 2014) and Aquacrop (Maniruzzaman et al., 2015; Mondal et al., 2015a) to estimate the sensitivity of rice and wheat productivity to projected temperature, precipitation, and atmospheric carbon dioxide, based on generic farming practices. A common limitation of these studies is that they tend to assess impacts on individual crops in isolation from interactions with other crops in a cropping system. They also largely fail to capture farm-specific contexts and actual farmer practice, making the modelling results insensitive to adaptation options.

The APSIM model (Holzworth et al., 2014) overcomes these limitations, and in recent years APSIM has seen more widespread use to model the impact of climate change on rice-based cropping systems in Asia (e.g. Gaydon et al., 2014b, 2017; Hochman et al., 2017a, 2017b; Poulton et al., 2016). APSIM's ability to model salinity dynamics in rice is a very new development (Radanielson et al., 2018), a feature that other models are lacking, so there are limited modelling studies on the impact of salinity on rice-based cropping systems.

In summary, there is a lack of reports that assess the combined impacts of climate and salinity change on cropping system performance from both yield and economic perspectives, under farmers' current management practices and/or with adaptive responses at the farm

level. We used bio-economic modelling, combining biophysical and economic modelling, to assess the future impact of climate change and salinization on the sustainability of ten current and potential cropping systems representative of large areas of south-west coastal Bangladesh. Although both climate change and salinization can be considered exogenous trends, and salinization is in part attributable to climate change, in principle there is the potential to mitigate salinity independently at the regional level, while changes in climate (rainfall, temperature, sunshine hours, and CO_2) necessarily require adaptive responses. We present our findings in three papers. This paper reports on the biophysical modelling that was undertaken based on farmers' current practices. The second paper (Kabir et al., 2017) incorporates these biophysical results into crop budgets to model the economic impacts. The third paper (Kabir et al., 2018) analyses the biophysical and economic impacts of the scenarios assuming adaptive responses on the part of farmers. The findings reported in those papers – in particular, (i) impacts of climate change and salinity on yields and farm income and (ii) some plausible adaptation options to escape the adverse environmental consequences – could be of use in other large saline or non-saline coastal areas or deltas of South and Southeast Asia where similar conditions prevail.

2. Materials and methods

Case studies of two representative villages in Khulna District were undertaken to assess current cropping practices and their economic viability. The villages selected represent a wide range of typical climate, soil and cropping conditions prevailing in south-west Bangladesh. Five climate scenarios were considered together with three salinization scenarios. The impacts of climate change and salinity were disaggregated in the modelling.

2.1. Modelling framework

The methodological framework used for the biophysical modelling reported in this paper is illustrated in Fig. 2. The Agricultural Production Systems sIMulator (APSIM) modelling framework (see details in Section 2.7) was used for simulating both climatic and salinity impacts on wet-season (WS), dry-season (DS), and early-wet-season (EWS) rice crops, as APSIM has recently been enhanced to model the rice crop salinity response (Radanielson et al., 2018), beyond its inherent ability to simulate climate and enviromenal (crop management, soil moisture, nutrient) impacts. However, for maize, sunflower, and wheat, APSIM was employed to simulate only the climate change impacts as the current versions of APSIM-Wheat, APSIM-Maize, and APSIM-Sunflower do not respond to the level of soil salinity. Instead, the salinity impact was assessed by developing salinity response functions from studies in the literature and applying those, post-simulation, to the crop yields simulated in the absence of salinity. The future performance of some existing major DS crops, namely, watermelon and pumpkin, were extrapolated from data available in the literature and expert knowledge as they are not currently modelled within APSIM. Likewise, the future performance of the DS brackish-water shrimp activity was extrapolated from available evidence rather than explicitly modelled.

2.2. Village and household case studies

Two villages in Dacope Upazila in Khulna District with contrasting farming systems were selected for study. Between them, the two villages encompass the main types of farming that are currently practised in the south-western coastal zone (Fig. 1), hence they provided a basis for assessing potential changes in farming systems with climate change and salinization. In the first village – Shaheberabad – arable land is intensively used for WS rice and DS non-rice cropping because of low levels of salinity, the availability of freshwater irrigation for DS cropping, and better access to extension services and markets. The second village – Uttar Kaminibasia – practises WS rice/fish farming and brackish-water shrimp farming in the DS due to high levels of salinity with no fresh water for irrigation. This village had better access to tidal water throughout the year but poorer access to markets and extension

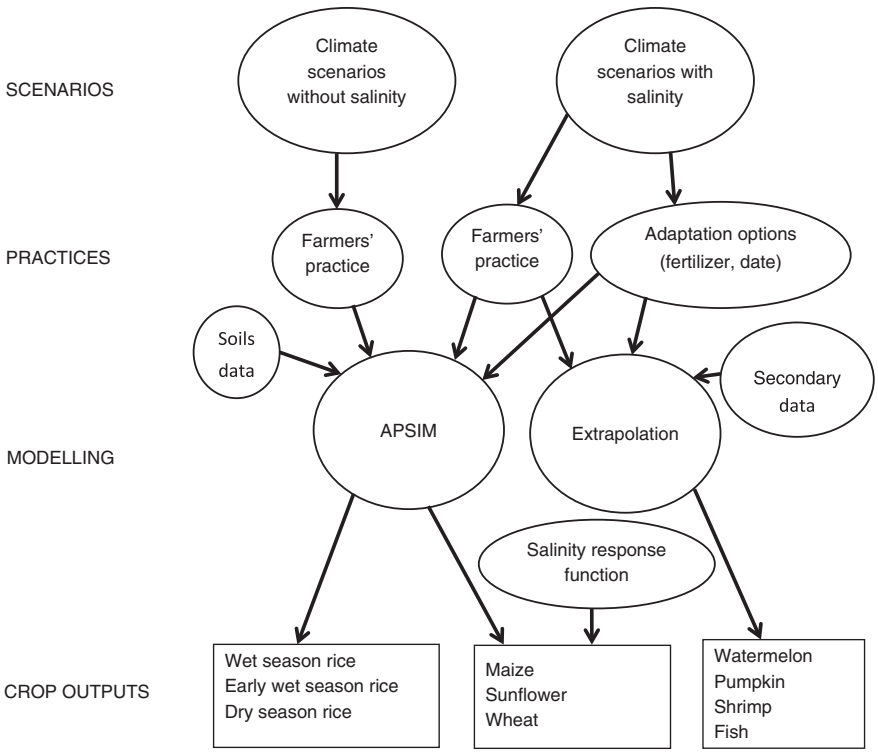

Fig. 2. Biophysical modelling framework of climate and salinity change on crop production. Note shrimp and fish are only discussed in the companion papers. Kabir et al. (2017) and Kabir et al. (2018).

services.

Farm-level data were collected through three case studies of farmers in each of three different farm-size classes, that is, small (< 0.6 ha), medium (0.6–2.6 ha), and large (> 2.6 ha), in each of the study villages (i.e., 18 case studies in total). The case studies involved face-to face interviews with each farmer using a semi-structured questionnaire. Farmers were asked for details of their current cropping activities, including detailed management practices, decision points, factor inputs and costs, labour use and costs, and crop yields and prices (typical, high, and low values). Details on the methods and results of the economic research are provided in Paper 2 (Kabir et al., 2017).

2.3. Cropping systems

Six cropping systems currently practised in the two case-study villages were assessed. In addition, a number of projects have trialled maize, sunflower, and wheat as potential DS crops in south-west Bangladesh (Rawson, 2011; Dalgliesh et al., 2012; Mainuddin et al., 2013; CSISA, 2015) and obtained promising results. For example, maximum wheat yields from the saline and non-saline areas of the south-western coastal zone (e.g., Khulna and Satkhira) are reported to range from 2.7 to 3.9 t/ha (Rawson, 2011; Mainuddin et al., 2013; Krupnik et al., 2015a; Krupnik et al., 2015b), indicating the yield potential of wheat in south-western Bangladesh. Similarly, highest sunflower yields range between 2.3 and 3.7 t/ha and maize yields range between 6.9 and 8.8 t/ha in Khulna and Patuakhali (Rashid et al., 2014; Mondal et al., 2015b). Moreover, the key informant farmers of the case-study villages recognized these as potential crops. Thus, maize, sunflower, and wheat systems were included in the simulation scenarios as potential future crops in the face of decreased access to freshwater irrigation, elevating soil and water salinity, and increased climatic risks. The key features of the potential crops are that they are significantly less irrigation-intensive than DS rice, require less fertilizer and pesticide than the major existing DS crops (for example, watermelon) (Kabir, 2016), and maize and sunflower are relatively tolerant to drought, pests and diseases, and salinity (Kabir, 2016; Bita and Gerats, 2013; Mathys and McDonald, 2013; Vanaja et al., 2011; Kotuby-Amacher et al., 2000). On the other hand, farmers of Shaheberabad had stopped cultivating DS rice 5–8 years previously, mainly due to the availability of profitable substitute crops requiring less irrigation. Thus, ten cropping systems were examined – six existing, one former, and three potential cropping systems (Table 1). These were each assessed under farmers' current management practices in each village.

2.4. Climate scenarios

There are many projected climate scenarios used in estimating the impacts of climate change globally. Two emissions scenarios, namely, A2 and B1 from the IPCC's Special Report on Emissions Scenarios (SRES), were used to assess associated climate change impacts on crop production (IPCC, 2001). IPCC ranked B1 as the least harsh climate scenario and A2 as the second harshest climate scenario out of six scenarios (IPCC, 2001). The harsher climate scenario A2 was treated as the "pessimistic" scenario for this study while B1 was used to provide an "optimistic" climate scenario, using specific projections for Bangladesh (Karmalkar et al., 2012). The modelling was conducted for a historical climate period (1984–2013) and two future periods – 2030 and 2060 – giving five climate scenarios in all – historical, 2030 pessimistic (A2), 2030 optimistic (B1), 2060 pessimistic (A2), and 2060 optimistic (B1) as per IPCC (2007). At the time this study was conducted, the new IPCC scenarios had not yet been defined. The SRES scenarios used in this study relate to the RCP4.5 and RCP8.5 scenarios in AR5 (IPCC, 2013).

Daily climate data for Khulna station (latitude 22°47′ N and longitude 89°32′ E) from 1984 to 2013 were incorporated into APSIM for simulating historical crop performance, including minimum and maximum temperature, precipitation, relative humidity, and sunshine hours (converted to solar radiation in MJ $m^{-2} d^{-1}$) (Fig. 3).

Changes reported by Karmalkar et al. (2012) in the mean level of atmospheric CO_2, minimum and maximum temperatures, rainfall, and sunshine hours in 2030 and 2060, based on the two IPCC emissions scenarios (A2 and B1) were applied to the daily historical climate data to generate daily APSIM climatic input parameters for future cropping scenarios in four seasons – December to February (DJF), March to May (MAM), June to August (JJA), and September to November (SON) (Tables 2 and 3). This involved incrementing the daily parameter values in the historical climate data file by the appropriate value (the amount of change suggested by Karmalkar et al., 2012) and feeding into the APSIM model. It was noted that the time spans of the Karmalkar et al. (2012) climate baseline (1979–1999) and atmospheric CO_2 baseline (1980–2010) differed marginally from the historical climate baseline chosen for APSIM simulations (1984–2013). While it would have been ideal to use exactly the same baselines for each climate variable, we judged that the use of such slightly different baselines was unlikely to have significantly distorted the simulations.

2.5. Salinity scenarios

The impact of salinity, in particular on DS and EWS crops, was assessed across historical (2004–2014) and two future (2030 and 2060) salinity scenarios. In addition, a "no salinity" scenario was used to separate out the offsetting effects of climate change. Both the "with-" and "without-salinity" scenarios were developed for the DS and EWS crops as soil and water salinity substantially affect the crops grown in those seasons. However, only the 'without-salinity' scenario was developed for WS rice. This is because the crop is essentially free from adverse salinity impacts as soil and water salinity fall to very low levels in the WS after the commencement of monsoon precipitation.

The Bangladesh Soil Resources Development Institute (SRDI) has recorded reliable monthly mean soil salinity data for Batiaghata Sub-district for 2004–2014 (Fig. 4a). Due to the unavailability of recorded soil salinity data for Dacope Sub-district, the Batiaghata sub-district data were entered in the APSIM input files for modelling current impacts of salinity on DS rice and EWS rice. The Batiaghata data were used with some confidence because the soil salinity level of this location was consistent with one year's data collected from the case-study villages in Dacope Upazila (Kabir et al., 2016). The impact of salinity on other DS crops such as maize, sunflower, and wheat was assessed through a custom-developed salinity response function, applied to APSIM outputs (as discussed in Section 2.6).

However, the extrapolation of future (2030 and 2060) soil salinity scenarios is extremely difficult, mainly because the trend analysis of historical soil salinity data (2004–2014) gives unclear results. Even the

Table 1
Cropping systems assessed for Shaheberabad and Uttar Kaminibasia. Note shrimp component in P6 only discussed in companion papers II and III (Kabir et al., 2017 and Kabir et al., 2018).

Cropping system	Wet season[a] (WS)	Dry season (DS)	Early wet season (EWS)	Status
P1	Rice	Watermelon	Fallow	Existing
P2	Rice	Fallow	Fallow	
P3	Rice	Pumpkin	Fallow	
P4	Rice	Watermelon	Rice	
P5	Rice	Pumpkin	Rice	
P6	Rice/fish	Shrimp	Shrimp	
P7	Rice	Rice	Fallow	Former
P8	Rice	Maize	Fallow	Potential
P9	Rice	Sunflower	Fallow	
P10	Rice	Wheat	Fallow	

[a] WS rice is termed T. Aman, DS rice is termed Boro and EWS rice is termed Aus in Bangladesh.

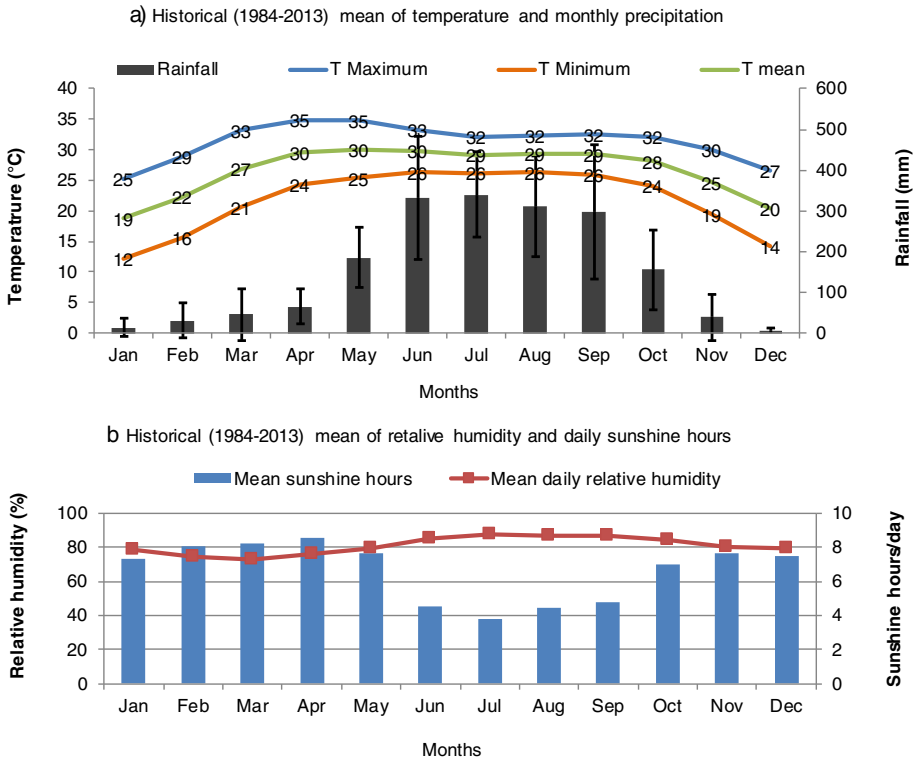

Fig. 3. Mean of historical (1984–2013) temperature, rainfall, relative humidity and sunshine hours for Khulna (Source: Bangladesh Metrological Department).

Table 2
Forecast changes to daily minimum and maximum temperatures during each season, under different climate scenarios.

Season	Mean temp. 1970–99 (°C)	Climate scenario	2030		2060	
			Min	Max	Min	Max
DJF	18.7	A2	1.1	0.5	2.4	1.2
		B1	0.9	0.5	1.9	0.9
MAM	26.5	A2	1.2	0.6	2.7	1.3
		B1	1.1	0.5	1.7	0.9
JJA	27.4	A2	1.1	0.5	2.4	1.2
		B1	1.2	0.6	1.7	0.9
SON	25	A2	0.9	0.5	2.3	1.1
		B1	1.1	0.5	1.6	0.8

Source: Karmalkar et al. (2012 p. 4), Note: DJF – December to February), MAR- March to May, JJA- June to August and SON- September to November.

monthly DS soil salinity data for a given field on a specific date fluctuates widely from year to year due mainly to differences in rainfall around the soil sample collecting dates. Besides, soil salinity varies significantly both spatially (horizontally and vertically) and with time (Mainuddin et al., 2013). For modelling, we assumed that plants were exposed to average values in each field, varying by the month (Fig. 4). No published studies of projected soil salinity levels were available at the time of conducting the analysis. However, an SRDI (2012) report suggests that soil salinity is not just a trend for one site; rather there is a spread in the soil salinity level across the coastal region that is significantly affecting crop choices. The overall salinity-affected area has increased to around 63% of the total coastal arable land in 2009 from around 49% in 1973. The extent of moderate (salinity level 3 + salinity level 4) to high (salinity level 5) saline areas is increasing (about 15% in 1973 to 43% in 2009) while the extent of low (salinity level 1 + salinity level2) saline areas is decreasing (about 85% in 1973 to about 57% in 2009) (SRDI, 2012 p. 6). Besides, salinity intrusion will likely be further elevated during the current century due to sea-level rise in Bangladesh (WB, 2013).

These data indicate that the overall salinity-affected area in coastal Bangladesh is increasing, that less-saline areas are becoming more saline, and that these trends will continue, with potentially larger impacts on cropping than climate change. In the modelling reported here,

Table 3
Forecast atmospheric CO_2 levels and changes to daily precipitation during each season, under different emission scenarios.
Source: IPCC (2007), Karmalkar et al. (2012), p. 4.

Season	Mean rainfall (mm) (1970–99)	Mean CO_2 (ppm) (1980–2010)	Emission scenario	2030		2060	
				CO_2 (ppm)	% change rain from base period	CO_2 (ppm)	% change rain from base period
DJF	14.9	362	A2	451	−10	580	−5
			B1	437	−14	509	6
MAM	158.9	362	A2	451	0	580	1
			B1	437	3	509	3
JJA	476.7	362	A2	451	2	580	2
			B1	437	0	509	3
SON	172	362	A2	451	−4	580	2
			B1	437	−4	509	1

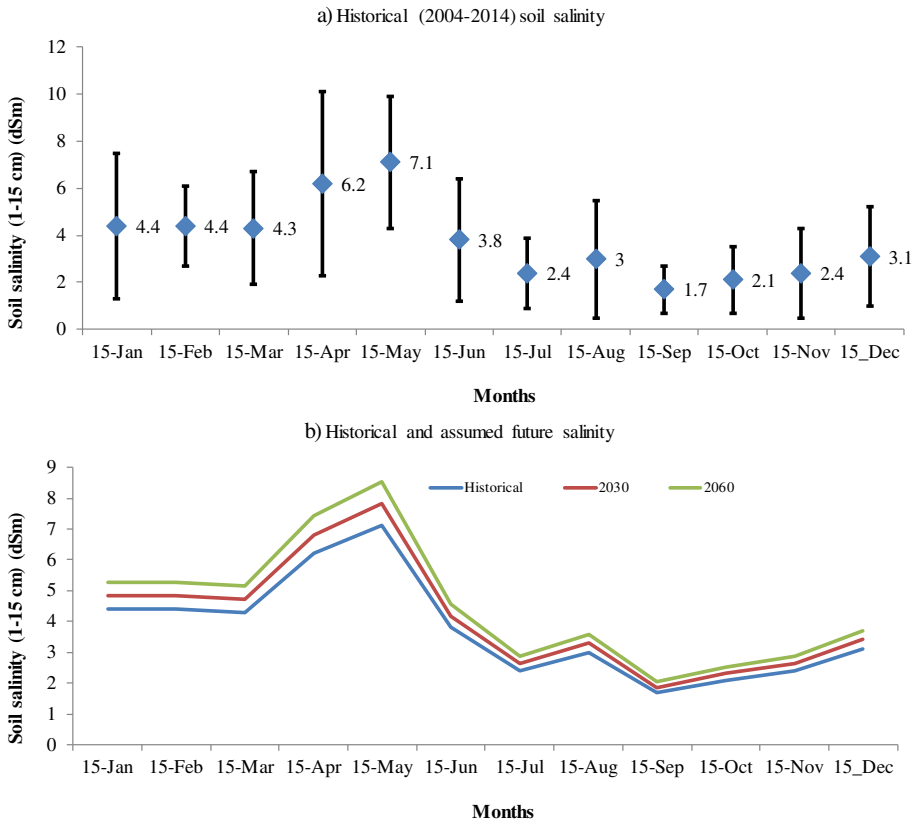

Fig. 4. (a) Historical (2004–2014) soil salinity in the 0-15 cm soil layer at Batiaghata, Khulna, including season-season variability and (b) assumed future soil salinity for 2030 and 2060 at same location. The blue line represents the historical data as in Panel (a). Source: Soil Resources Development Institute, Bangladesh. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

a 10% increase in soil salinity level over the next 15 years to 2030 was assumed, followed by a further 10% increase over the next 30 years to 2060 (Fig. 4b). Since the completion of this analysis, Dasgupta et al. (2015) employed an econometric model to project that soil salinity in Khulna will likely increase between 9 and 11% in 2030 and 26–33% in 2050 under low and high salinity scenarios. Hence the assumptions used in the modelling reported here, while crude, are close to the subsequent predictions of Dasgupta et al. (2015) and reflect the likely adverse trends.

2.6. Capturing the impacts of salinity on potential dry season crops

Linear regressions representing crop responses to soil salinity, using data from the literature, were used to derive salinity crop-response functions for maize, wheat, and sunflower (Fig. 5). The data used were from published studies which evaluated salinity impacts on grain yields and straw biomass. The salinity response functions in Fig. 5 were combined with average soil salinity levels (dS/m) during the actual growth period of the crops, given a range of possible planting dates to estimate percentages of salinity-free yields (Table 4). This was achieved by simulating the average period of crop growth for each planting date, then estimating the average salinity level to which the crop was actually exposed (as shown in Fig. 4), and finally reading the associated yield reduction percentage from the appropriate graph in Fig. 5. These percentages were applied to the APSIM-simulated yields and straw biomass (post-simulation) for maize, wheat, and sunflower to derive the production loss of the crops due to salinity across the three salinity scenarios (historical, 2030 and 2060).

2.7. The APSIM model – parameterisation and calibration

APSIM is a modular simulation framework which is capable of simulating biophysical processes in farming systems, and long-term impacts of climate change on biophysical factors which drive economic and ecological outcomes of management practices in the face of climate risks (McCown et al., 1996; Carberry et al., 2002; Keating et al., 2003; Holzworth et al., 2014). APSIM model performance has recently been robustly evaluated across a broad range of cropping systems in Asia and found to give reliable performance (Gaydon et al., 2012a, 2012b, 2017). The model is capable of simulating environmental risks, in particular implications of salinity for the rice crop (Radanielson et al., 2015, 2018; Gaydon et al., 2014a).

The historical meteorological data for Khulna presented in Fig. 3 were used as daily inputs to drive the model. Sunshine hour data were converted into solar radiation (MJ m^{-2} d^{-1}) using the method reported by Şen (2001) and Ahmed et al. (2009). The soil characteristics presented in Table 5 were used to parameterise the model. Soil data for Dacope were assumed to represent both villages as most soil chemical and physical properties were consistent between the villages, except for DS soil salinity (Kabir et al., 2016). Farmers' management practices (including sowing dates, field preparation, and fertilizer application) were obtained from interviews and incorporated into APSIM through its Manager Module. Crop varieties used in this study were calibrated using experimental data described in detail in Van Wensveen et al. (2015) and Gaydon et al. (2013, 2017).

2.8. APSIM model validation

APSIM has been widely tested and validated in rice-based cropping systems (Gaydon et al., 2014a, 2014b, 2017; Hochman et al., 2017a, 2017b; Poulton et al., 2016). The location-specific validation of simulation outcomes was performed using farm-level data collected during the case studies. APSIM simulations for the past 30 years (1984–2013) of yields for WS rice, EWS rice, DS rice, maize, sunflower, and wheat under the different cropping systems presented in Table 1 were compared with farmers' reported yields. The variability in crop yields from APSIM simulations was compared with farmers' estimated worst, typical, and best yields. In a separate study, Carberry et al. (2009) also

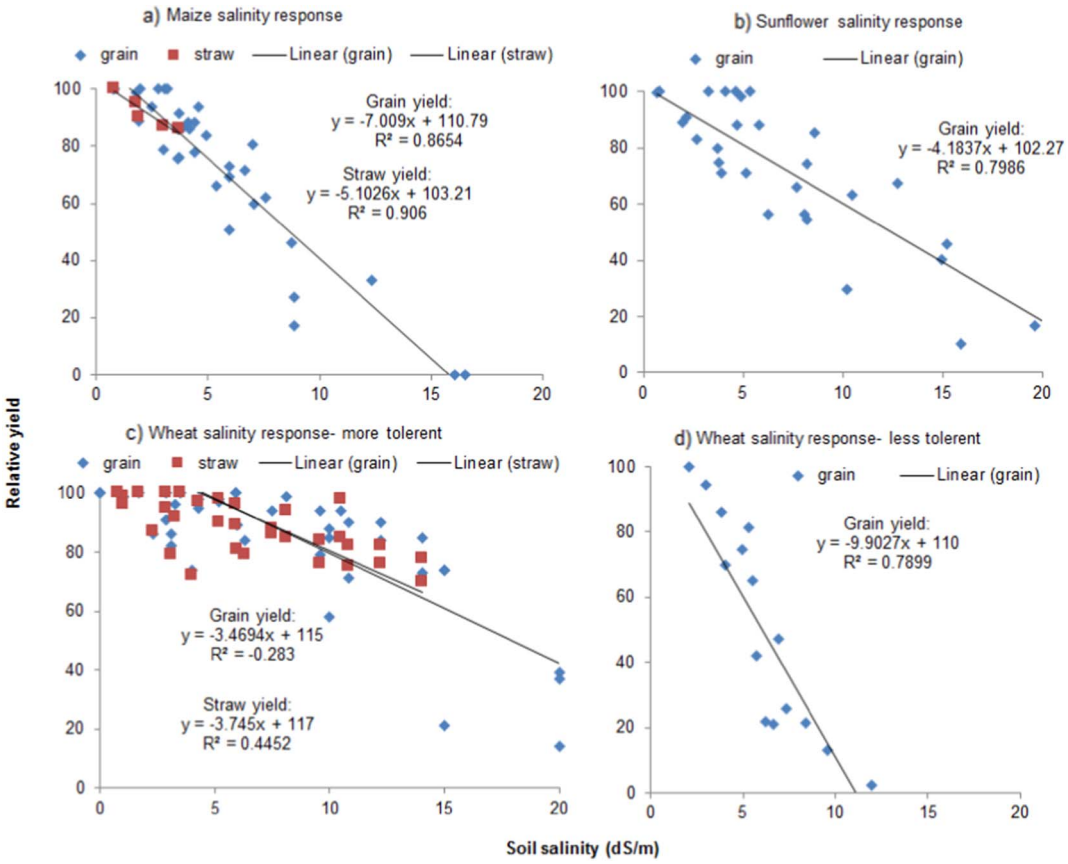

Fig. 5. Relative yield responses to salinity for dry-season crops.
Sources of data: wheat (Francois et al., 1988; Van Hoorn et al., 1993; Akram et al., 2002; Katerji et al., 2003; El-Hendawy et al., 2005), maize (Katerji et al., 1996; Katerji et al., 2003) and sunflower (Katerji et al., 1996; Katerji et al., 2003).

Table 4
Average historical soil salinity levels during the growth period of maize, wheat and sunflower sown at different dates collected from Soil Resources Development Institute, Bangladesh and the derived percentages of non-saline yield of the crops at those sowing dates across three salinity scenarios.
Source: Authors' estimation based on derived salinity response functions in Fig. 5.

Sowing date	Nov15	Nov26	Dec07	Dec15	Dec25	Jan 05	Jan 15	Jan 30	Feb 28	Mar31	Apr30
	Historical salinity levels (dS/m)										
Wheat	3.7	4.1	4.5	4.8	5.3	5.3	5.3	5.2	4.8	4.9	4.5
Maize	4.1	4.6	4.9	4.9	4.9	5.3	5.3	5.0	4.8	4.8	4.5
Sunflower	3.7	4.1	4.5	4.8	5.3	5.3	5.3	5.2	4.8	4.9	4.5
	% of salinity free yield										
Conventional wheat	78	75	70	66	61	61	61	62	66	65	69
Salt tolerant wheat	98	97	96	95	94	94	94	94	95	95	96
Maize	84	81	78	78	78	75	75	77	79	79	81
Sunflower	99	97	95	93	91	91	91	91	93	93	95
	Salinity levels (dS/m) in 2030										
Wheat	4.1	4.5	4.9	5.3	5.8	5.8	5.8	5.7	5.2	5.4	5.0
Maize	4.5	5.0	5.4	5.4	5.4	5.8	5.8	5.5	5.2	5.2	5.0
Sunflower	4.1	4.5	4.9	5.3	5.8	5.8	5.8	5.7	5.2	5.4	5.0
	% of salinity free yield										
Conventional wheat	74	70	65	60	54	54	54	56	61	60	64
Salt tolerant wheat	97	96	95	94	92	92	92	92	94	93	95
Maize	81	77	74	74	74	71	71	73	76	76	78
Sunflower	97	95	92	90	88	88	88	88	91	90	92
	Salinity levels (dS/m) in 2060										
Wheat	4.5	4.9	5.4	5.8	6.3	6.3	6.3	6.2	5.7	5.9	5.4
Maize	5.0	5.5	5.9	5.9	5.9	6.3	6.3	6.0	5.7	5.7	5.4
Sunflower	4.5	4.9	5.4	5.8	6.3	6.3	6.3	6.2	5.7	5.9	5.4
	% of salinity free yield										
Conventional wheat	70	65	59	55	48	48	48	50	56	54	59
Salt tolerant wheat	96	95	93	92	90	90	90	91	92	92	93
Maize	78	74	71	71	71	67	67	70	72	72	74
Sunflower	95	93	90	88	85	85	85	85	88	87	90

Table 5
APSIM soil parameterisation used in simulations for Dacope, Khulna Division, Bangladesh.
Source: Adapted from Van Wensveen et al. (2015).

Soil Layer (cms)	BD (g cc^{-1})	Air Dry (mm mm^{-1})	LL15 (mm mm^{-1})	DUL (mm mm^{-1})	SAT (mm mm^{-1})	KS (mm day^{-1})	OC (Walkley Black %)	pH ()
0–15	1.426	0.128	0.255	0.385	0.461	25.0	0.9	7.5
15–30	1.418	0.204	0.255	0.388	0.440	1.0/20.0[a]	0.7	7.8
30–60	1.422	0.255	0.255	0.388	0.427	20.0	0.5	7.7
60–90	1.409	0.255	0.255	0.393	0.433	20.0	0.2	7.7
90–120	1.398	0.255	0.255	0.397	0.436	20.0	0.06	7.7
120–150	1.388	0.255	0.255	0.398	0.444	20.0	0.03	7.7

BD – bulk density; all soil moisture contents are in volumetric terms:- 'Air Dry' – minimum moisture content to which soil can air-dried; 'LL15' – 15-bar lower limit, moisture retained under a 15.0 bar suction; 'DUL' – field capacity, moisture retained at 0.33 bar suction; 'SAT' – saturated moisture content; 'KS' – saturated percolation rate; 'OC' – organic carbon.
[a] KS set to 20.0 mm day^{-1} after end of transplanted rice crops to simulate breakup of plough pan with tillage, then reset to 1.0 mm day^{-1} during puddling phase each year.

validated APSIM-simulated yields by comparing them with yields of commercial crops in farmers' fields (in Australia) rather than in experimental plots in order to increase farmers' confidence in modelling outcomes. The worst seasonal yield was taken as the average of the lowest 20% of simulated yields, the typical seasonal yield as the average of the middle 60% of simulated yields, and the best seasonal yield as the average of the best 20% of simulated yields.

The APSIM-simulated and farmer-estimated typical seasonal grain yields with seasonal variability under different cropping systems were reasonably consistent (Fig. 6). Hence we confidently claim that the model simulates realistic outcomes for historical conditions, and recent evidence also suggests reliability for simulation of future conditions (simulation of crop response to increased CO_2 and temperatures; Gaydon et al., 2017). As APSIM does not simulate pests and diseases (which the farmer estimates will invariably include), the fact that APSIM usually simulated slightly higher yields, and with less variability, is to be expected.

The APSIM model was then applied to simulate impacts of changes in climate and (where the model was capable) of salinity for the major crops – rice, maize, wheat, and sunflower – under the specified cropping patterns. Table 6 presents details of the crop managements imposed in the APSIM model for our study. Yields of watermelon, pumpkin, and brackish-water shrimp under changed future conditions were based on previous published and unpublished research as well as the perceptions of key informants and expert personnel experienced in coastal farming systems. The basis for these estimates is discussed following the presentation of modelling results in the following section.

3. Results

3.1. Impacts of climate change and salinization on crop productivity

3.1.1. Wet-season rice

The modelling indicates that the impact of climate change on WS rice yield until 2060 will be limited. The overall impact on yield was relatively slight, and there was no pronounced difference between the pessimistic (A2) and optimistic (B1) climate scenarios (Fig. 7). The yield loss of WS rice in the four future scenarios was only 3–5% of historical yield. This was likely due to a combination of reduced life span and increased heat-related grain sterility, even in the face of the positive carbon-fertilisation effect of increased atmospheric CO_2. In some cropping systems (P4, P5, P9, P10), simulated yields under the pessimistic scenario in 2060 were slightly higher than historical yields, presumably because the fertilizer effects of increased atmospheric CO_2 more than offset the small yield loss due to increased temperature. Also, the maximum temperatures in 2060 were still below the yield-loss thresholds for the reproductive phase of the crop.

The variation in rice yield between cropping systems was due to variation in the date of planting and availability of residual fertilizers. The yield of WS rice was higher in the cropping systems with only two crops such as P1, P2 and P6 compared with the cropping systems involving three crops such as P4 and P5 across the five climate scenarios (Fig. 7). When WS rice is incorporated in a two-crop system it can take up residual nutrients from the preceding DS crop (e.g., watermelon, pumpkin, or shrimp) while in the three-crop system the crop duration of the photoperiod-sensitive WS rice varieties is shortened by 1–2 weeks due to transplanting delay and the fact that EWS rice leaves less fertilizer in the soil.

3.1.2. Dry-season rice

Considering the yield with salinity scenarios, climate change had minimal impacts on the yield of DS rice in 2030 and caused only a slight yield loss (3–6%) in 2060 (Fig. 8). The yield variation between the pessimistic (A2) and optimistic (B1) emission scenarios was also not pronounced. Though the maximum temperature in the 2060 climate scenarios rises to near the damage-threshold during the critical or reproductive phase, it infrequently exceeded it and consequently the yield loss was not severe. This can perhaps be explained by the adverse effects of climate change being offset by the positive effects of increased atmospheric CO_2 and precipitation during the reproductive phase. The additional CO_2 provides a fertilizer effect and the extra precipitation creates favourable conditions to take up soil nutrients and reduces soil salinity and moisture stress.

However, the results indicate that salinity was responsible for substantial yield loss under the farmers' management practice (planting date, fertilizer rate, and irrigation). It can be noted that with historical climate in the absence of salinity changes, yield would increase by about 2.3 t/ha (Fig. 8). Climate change without salinity gives, 1.8–1.9 t/ha higher yield for the 2030 climate scenarios and 2.0–2.1 t/ha higher yield for the 2060 climate scenarios, compared with yields in the saline environment for the same scenarios. Thus, yield loss due to salinity was 68% for the historical climate scenario, 52–55% across 2030 climate scenarios and 62–63% across 2060 climate scenarios. This result is consistent with the perception of farmers that salinity is the crucial bottleneck for DS rice in the coastal lands.

3.1.3. Early wet season rice

While the substantial effect of salinity is still evident, EWS rice performed better (13–14% higher yield in 2030 conditions and 18–20% higher yield in 2060 conditions) across the four future climate scenarios with no pronounced yield variation between the pessimistic (A2) and optimistic (B1) emission scenarios (Fig. 9). The negative impact on EWS rice yield from salinity is substantial, but in the final analysis the negative impact of salinity was outweighed by the advantages of future increased rainfall during the season (reducing drought stress as this is a rain-fed crop), as well as CO_2 fertilisation. Climate change in a non-saline environment gave 44–45% higher yield in 2030 than climate change with salinity, and 39–43% higher yield in 2060. That is, with crop management constant, yield loss due to salinity was 1.2–1.3 t/ha across the four future climate scenarios. Yield loss due to salinity under historical climate was 1.0 t/ha. These results indicate that salinity remains the crucial bottleneck for rainfed EWS rice under farmers' current

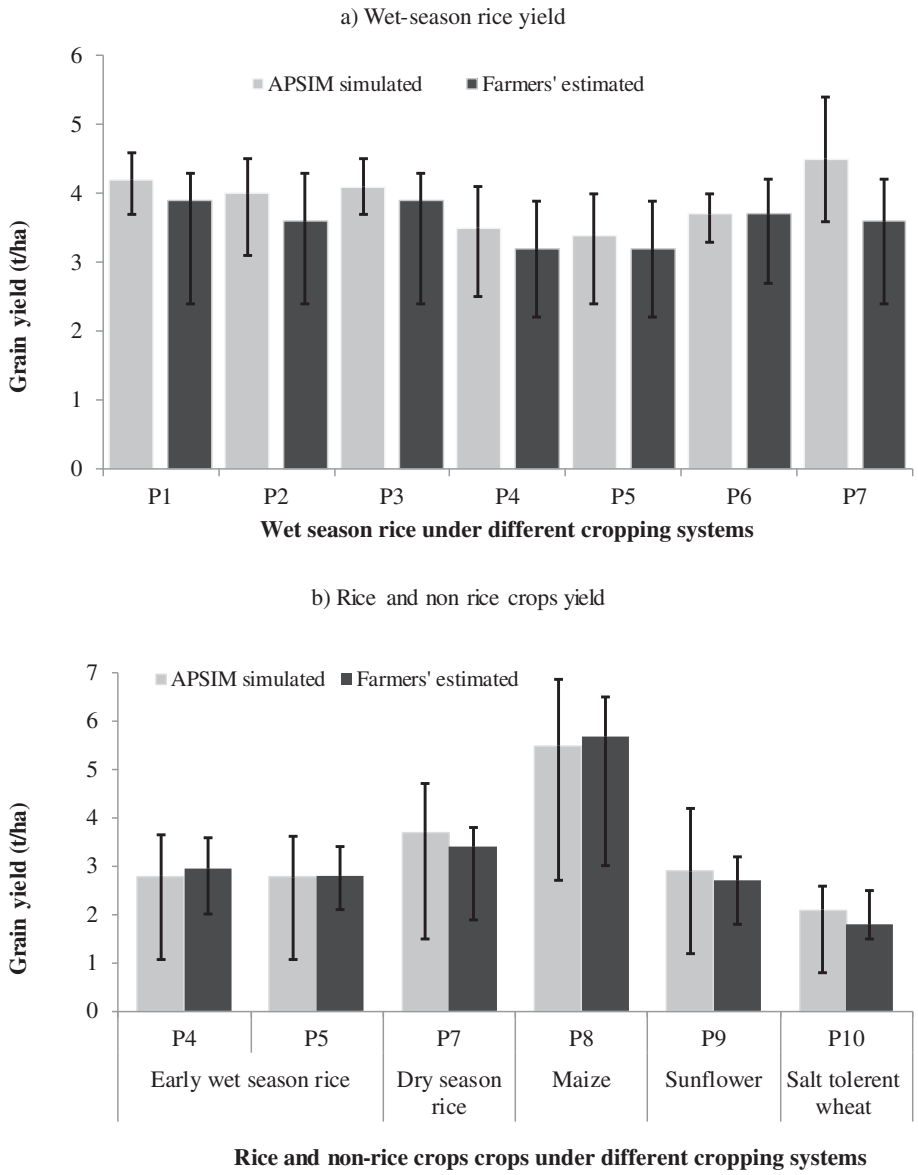

Fig. 6. Comparison between APSIM-simulated and farmer-estimated grain yields for different cropping systems. Error bars indicate variability around mean of simulated yields (30 years).

cropping practices. Conversely, if salinity could somehow be removed from the cropping environment or a salt-tolerant variety could be introduced, the yield gain would be substantial.

3.1.4. Potential dry-season grain crops

(a) Maize

In the absence of salinity, maize yield was significantly higher across all climate scenarios compared with yields in the saline environment for the same scenarios. The yield increase due to no salinity was about 27% (1.4 t/ha) under historical conditions, 38% (2.1–2.2 t/ha) in 2030, and 45% (2.8–2.9 t/ha) in 2060 (Fig. 10). On the other hand, in the presence of salinity and relative to historical conditions, maize yield increased by 0.7–0.8 t/ha (15–16%) in the 2030 climate scenarios and 1.0–1.4 t/ha (22–27%) in the 2060 climate scenarios (Fig. 10). The yield differed little between the pessimistic (A2) and optimistic (B1) climate scenarios. The results indicate that the net effect of climate change and salinization on maize yield was positive but there was an increase in seasonal variability.

(b) Sunflower

With salinity, sunflower yield decreased by 0.2–0.3 t/ha (7–10%) in 2030 and 0.3–0.5 t/ha (17%) in 2060, compared with historical climate (Fig. 11). The yield differed little between the pessimistic (A2) and optimistic (B1) scenarios. The results indicate that the net effect of climate change and salinization on average yield was relatively slight. In the absence of salinity, sunflower yield was up by about 10–18% across all five climate scenarios. The yield loss due to salinity was therefore about 0.28 t/ha in historical climate, 0.34–0.35 t/ha in 2030 and 0.40–0.42 t/ha in 2060. These results suggest that sunflower is relatively less sensitive to salinity compared with other crops such as DS rice, maize, and EWS rice.

(c) Wheat

The yield of both the salt-tolerant and conventional varieties of wheat was simulated across the five climate scenarios, with and without salinity. The response of both varieties to climate change was the same; however, the sensitivity of the conventional variety to salinity was substantial, with a decline of 48–54% across the future scenarios (Table 4). Hence only the yield of the salt-tolerant variety is discussed in this section.

There was a slight yield loss (6–8%) for the 2030 scenarios but the

Table 6
Crop management details imposed in APSIM model.

Crop	Management details imposed in APSIM
WS Rice	• Variety BR23; simulated sowing range 20th Jul – 11th Aug, seedlings transplanted after 25d in nursery, 1 seedling per hill, 16 hills per m^2 • N Fertilizer 165 kg ha^{-1} urea, in 2 splits, 75 kg ha^{-1} (15–20 DAT), 90 kg ha^{-1} (at heading stage) for most patterns except P1 and P3, only 75 kg urea (at heading stage) • No irrigation, rainfed only • Range of harvest dates 3rd Dec – 15th Dec • Stubble grazed
EWS Rice	• Variety BR48; simulated sowing date 15th Mar - 26th Apr, seedlings broadcast to achieve density of 5 plants m^{-2} • N Fertilizer 131 kg ha^{-1} urea, in 2 splits, 56 kg (35 DAS) and 75 kg (60 DAS) • No irrigation, rainfed only • Range of harvest dates 3rd Jul – 11th Aug • Stubble grazed
DS Rice	• Variety BRRI-Dhan 47; simulated sowing 1st January, seedlings transplanted after 33d in nursery, 1 seedling per hill, 25 hills per m^2 • N Fertilizer 300 kg ha^{-1} urea, in 3 splits, 100 kg (29 DAS during puddling and land prep), 100 kg (54 DAS), and 100 kg (101 DAS) • Fully irrigated, re-flooded each time pond went below 10 mm depth • Range of harvest dates 4th May – 12th May • Stubble grazed
Maize	• Variety BARI Hybrid 7; simulated sowing 15th Dec, density 7 plants per m^2, sowing depth 20 mm, row spacing 150 mm • N Fertilizer 413 kg ha^{-1} urea, in 3 splits, 109 kg at sowing, 152 kg (30 DAS), and 152 kg (50 DAS) • Irrigation 10 mm at sowing, then 60 mm applied on a 60 mm soil water deficit. Up to 6 irrigations applied • Range of harvest dates 1st May – 12th May • Stubble grazed
Sunflower	• Variety Hysun 33; simulated sowing 15th Dec, density 40 plants per m^2, sowing depth 20 mm, row spacing 75 mm • N Fertilizer 239 kg ha^{-1} urea, in 3 splits, 65 kg at sowing, 87 kg (30 DAS), and 87 kg (50 DAS) • Irrigation 10 mm at sowing, then 40 mm applied on a 40 mm soil water deficit. Up to 5 irrigations applied • Range of harvest dates 17th Mar – 12th Apr • Stubble grazed
Wheat	• Variety BARI gom 26; simulated sowing 18th Dec, density 150 plants per m^2, sowing depth 20 mm, row spacing 150 mm • N Fertilizer 240 kg ha^{-1} urea, in 3 splits, 75 kg at sowing, 90 kg (30 DAS), and 75 kg (50 DAS) • Irrigation 10 mm at sowing, then 40 mm applied on a 40 mm soil water deficit. Up to 4 irrigations applied • Range of harvest dates 23rd Apr – 30th Apr • Stubble grazed

DAS – days after sowing in nursery; DAT – days after transplanting.

yield loss increased to 18% under the pessimistic (A2) climate scenario in 2060 (Fig. 12). The yield variation between the pessimistic (A2) and optimistic (B1) emission scenarios was not pronounced. The yield in the absence of salinity was slightly higher than with salinity. The yield loss due to salinity under the historical climate was 7% (0.1 t/ha), slightly increasing to 9% (0.2 t/ha) in 2030 and 11% (0.2 t/ha) in 2060. These results indicate that climate and salinity impacts on salt-tolerant wheat would not be severe through to 2060.

3.1.5. Vegetable and fruit crops

Earlier in the paper, Fig. 3 and Table 2 show historical mean monthly minimum and maximum temperatures in Khulna District during the dry season (mid-February-May) of 16 and 35 °C, which are consistent with the acceptable temperature range for the growth phase of watermelon and pumpkin (Ramos et al., 2011, p. 60 citing Krug, 1997). However, the historical mean monthly temperature in Khulna during the reproductive phase of watermelon and pumpkin (April) was 30 °C which is 3–5 °C higher than the optimal temperature for these crops (Dr A T M Masud, BARI, personal communication). Besides, Karmalkar et al. (2012) projected that mean monthly seasonal temperature during the March–May season in Bangladesh will rise by 0.9 °C (A2 scenario) or 0.8 °C (B1 scenario) in 2030 and by 2.0 °C (A2) or 1.3 °C (B1) in 2060. Hence the mean monthly seasonal temperature across the 2060 climate scenarios is very likely to exceed both the optimal growth and reproductive temperature range for pumpkin and watermelon in the coastal areas of the country. Only a few degrees in temperature above the threshold level can substantially affect reproductive development (pollen release and fruit set) and efficacy (pollen viability) for many vegetables, including watermelon and pumpkin, and create physiological disorders (Ramos et al., 2011). Increased temperature outside the optimal range might change the growing periods, create greater evaporative demand, and cause pollination problems in horticultural crops like watermelon and pumpkin, leading to reduced yields and crop quality (Deuter, 2008; Ramos et al., 2011). It can be concluded that rising temperatures might become a critical bottleneck for growing pumpkin and watermelon in coastal land after mid-century.

In addition, AVRDC (1990) reported that watermelon and pumpkin are not tolerant to soil salinity above EC 4–6 dS/m). Also, increasing salts in the soil reduces the availability of soil moisture to plants, so crops grown in saline soils need more frequent irrigation than the same crops in normal soils.

Colla et al. (2006) reported that total fruit yield and mean fruit mass of watermelon are significantly affected by salinity levels ranging from 2.0 to 5.2 dS/m. The historical (2004–2014) mean monthly soil salinity level in Batiaghata, Khulna, during the DS cropping period (February–May) was higher than this at 4.4–7.1 dS/m (Fig. 4). The projected soil salinity levels across 2030 (4.48–7.81 dS/m) and 2060 (5.16–8.52 dS/m) were higher than the threshold soil salinity level for the somewhat salt-tolerant vegetable crops (Fig. 4). Key informants felt that the effect of climate change and salinization on watermelon and pumpkin would be substantial, with watermelon affected more than pumpkin as pumpkin is relatively drought tolerant and somewhat salt tolerant.

Based on these considerations, the estimated historical and extrapolated performance of watermelon and pumpkin across the five climate scenarios is presented in Table 7. It was projected that watermelon yield would decrease by 12–15% in 2030 and a further 25–30% in 2060, while pumpkin yield would decrease by 7–10% in 2030 and a further 12–15% in 2060.

3.1.6. Shrimp and fish

Shrimp and fish were incorporated in cropping system P6 in Table 1, hence estimates of future yields were needed to complete the economic comparisons in Papers 2 (Kabir et al., 2017) and 3 (Kabir et al., 2018). There were few data on which to base the extrapolation of shrimp and fish yields. Aquaculture experts in Bangladesh commented that the

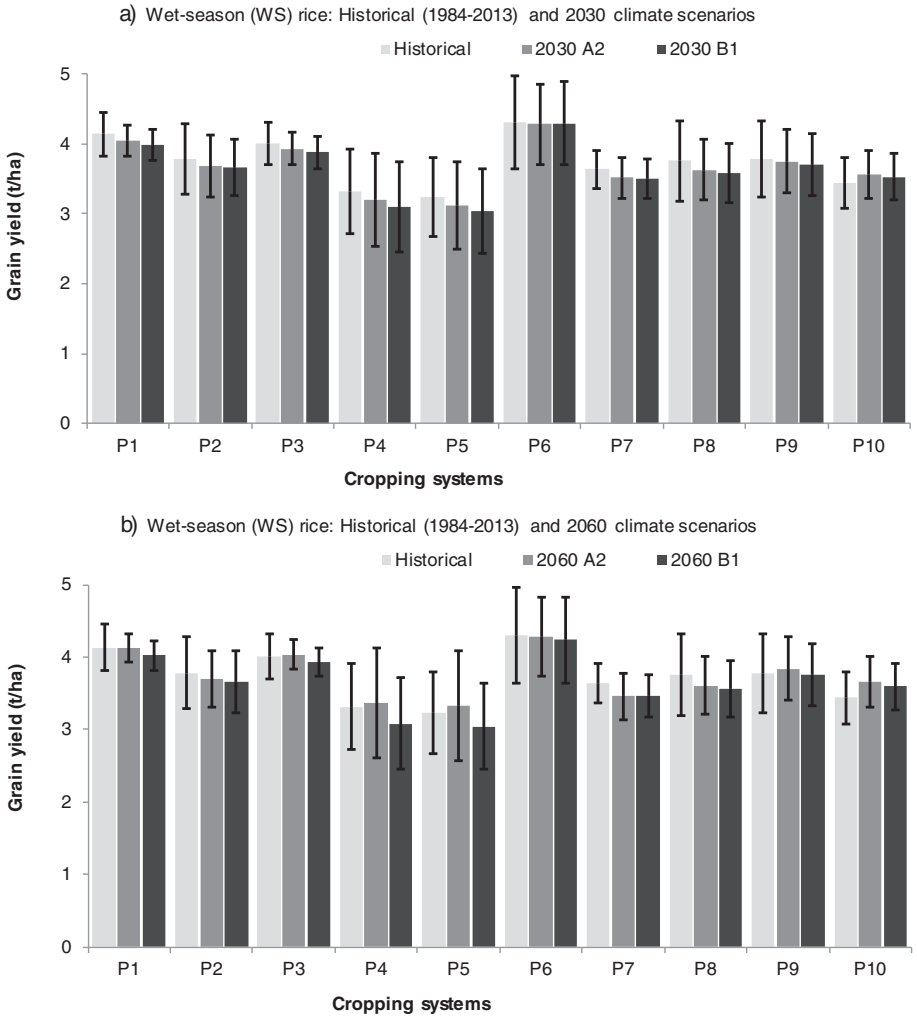

Fig. 7. APSIM simulated historical (1984–2013) and future (2030 and 2060) yield of wet season rice under pessimistic (A2) and optimistic (B1) climate scenarios. Error bars show variability of seasonal grain yield around the mean (30 years).

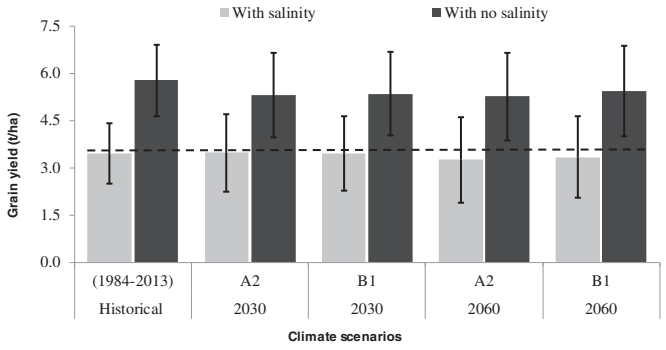

Fig. 8. APSIM simulated yield of dry season rice with and without salinity across the five climate scenarios. Note: Error bars show seasonal grain yield variability around the mean (30 years). Dotted line shows difference between historical yields with salinity and other yields with and in absence of salinity.

yield of brackish water shrimp and fish in coastal regions may not decrease, despite rising temperature. Moreover, it was reported that there is significant potential to further enhance the productivity of black tiger shrimp (Penaeus monodon) through improving cultural practices (feed and management) (Norman-Ĺopez et al., 2015). Based on these observations, it was projected that per hectare yields of cultured shrimp and fish would likely be unchanged until 2060 under farmers' current best practice despite harsher climate (especially rising temperatures) due mainly to increased access to tidal water because of sea-level rise, despite the effect of increasing temperatures.

4. Discussion

The modelling presented in this paper suggests that climate change has both positive and negative impacts on crop yields but salinity has substantial negative effects. Similarly, reviewing many climate change impact assessment studies covering a wide range of regions and crops, IPCC reported that the negative impacts of climate change on crop yields are more common than positive impacts (high confidence) (IPCC, 2014b). Our results indicate that, on average, the yield of rainfed WS rice in most cropping systems is projected to decrease by only 3–5% over the next 15–45 years due to a combination of reduced life span of plants and increased heat-related grain sterility, even in the face of the positive effect of increased atmospheric CO_2. However, it is likely that progress in plant breeding and selection would be able to overcome this relatively small decrease due to adverse environmental conditions. Similarly, rising temperature through to 2060 was not found to adversely affect the productivity of rainfed EWS rice (13–25% increase), irrigated DS rice (3–6% decrease), and irrigated DS crops including maize (5–27% increase), sunflower (7–17% decrease) and wheat (2–4% decrease).

By comparison, Thomas et al. (2013) simulated the impacts of climate change on various crops using the DSSAT model and projected

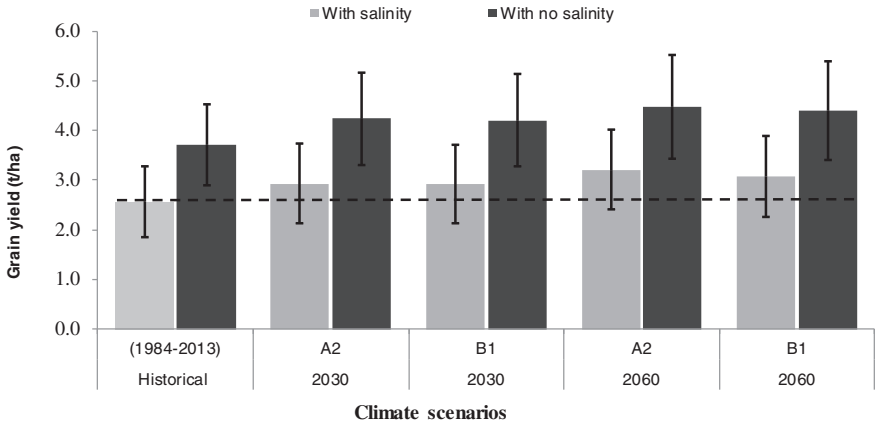

Fig. 9. APSIM simulated yield of early wet season rice with and without salinity across the five climate scenarios. Note: Error bars show seasonal grain yield variability around the mean (30 years). Dotted line shows difference between historical yields with salinity and other yields with and no salinity.

that yields of WS rice would decrease by 1–9% in Khulna in 2050 compared to the base year (2000), yields of DS rice would decrease by 2–11%, and yields of maize would increase by 2–4%. Basak et al. (2010), using the DSSAT model to simulate the impacts of climate change (a temperature increase of 5 °C above the 2005 base level) at the 2005 level of CO_2 (379 ppm), found that yields of DS rice may decrease by 21% in 2050 in south-western coastal Bangladesh. Basak et al. (2014), again using the DSSAT model, reported that yields of DS rice may decrease by 2–8% and 15–23% with temperature increases of 2 °C and 4 °C respectively over the baseline year and increased atmospheric CO_2 of 200 ppm. Ruane et al. (2013) using the CERES model reported that WS rice yield in Khulna was projected to decrease by 11%, DS rice yield by 21%, and EWS rice by 11% from around 2010 yields through to around 2040–2060 due to changes in temperature, precipitation, atmospheric CO_2, sea-level rise, and flooding. Ruane et al. (2013) also projected that wheat yield would decrease by 13% in Khulna over the same period.

Generally, our rice results lie within the same magnitude of variation. Some of these studies used earlier models that are more constrained in their ability to capture specific rice varieties, or were parameterised for generalised conditions. The majority of the models employed in these cited studies utilise atmospheric temperatures to calculate crop sterility losses, whereas in APSIM we represented the canopy temperature, which may be up to 6-7 °C cooler in fully-irrigated rice crops under dry conditions than the atmospheric temperature (Matsui et al., 2007). Failing to recognise the difference between canopy temperature and atmospheric temperature can lead to large overestimation in simulated yield loss in irrigated rice crops (Gaydon et al., 2017). In contrast, in our study we were able to parametrise APSIM to reflect more closely the local growing conditions, including relevant varieties and the temperature conditions to which their developing florets were exposed. We assumed 2 °C canopy cooling for assumed relative humidity of 60% during extreme high temperature days in southern Bangladesh (Van Oort et al., 2014, Fig. 1 p. 305). We also used observed local soil conditions and farmers' practices in terms of planting dates and nutrient and water management. APSIM provides greater versatility than other models to do this through its Manager Module. Consequently, we contend that our perhaps more optimistic rice yields are more plausible than previous modelling results.

Beyond rice, Yu et al. (2010), using CERES Rice and Wheat models, reported that yield loss of wheat in Khulna would likely be 10% by 2050. Likewise, Rosegrant et al. (2010), after analysing a wide range of published simulated data sets on projected impact of climate change on agricultural production, reported that, despite the large uncertainty, the weight of evidence was that climate change impacts on agricultural production would be mostly negative in South, Central, and Western Asia, and these regions would face declining wheat, rice, and maize yields. Sivakumar and Stefanski (2010) reported that the net cereal production for South Asian countries may decrease by between 4% and 10% by the end of this century even under the most conservative scenario, and that wheat and maize yield potentials in India are likely to decrease by 2–5% for increases in temperature of 0.5–1.5 °C. Similarly, Challinor et al. (2014) collated a wide range of published simulated data sets on projected changes to yields of major crops. They found a

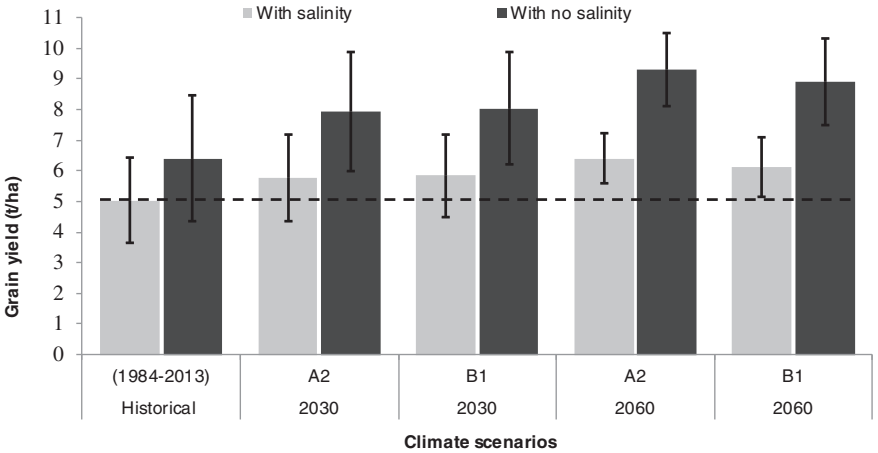

Fig. 10. APSIM simulated yield of maize with and without salinity across the five climate scenarios. Note: Error bars show seasonal grain yield variability around the mean (30 years). Dotted line shows difference between historical yields with salinity and other yields with and in absence of salinity.

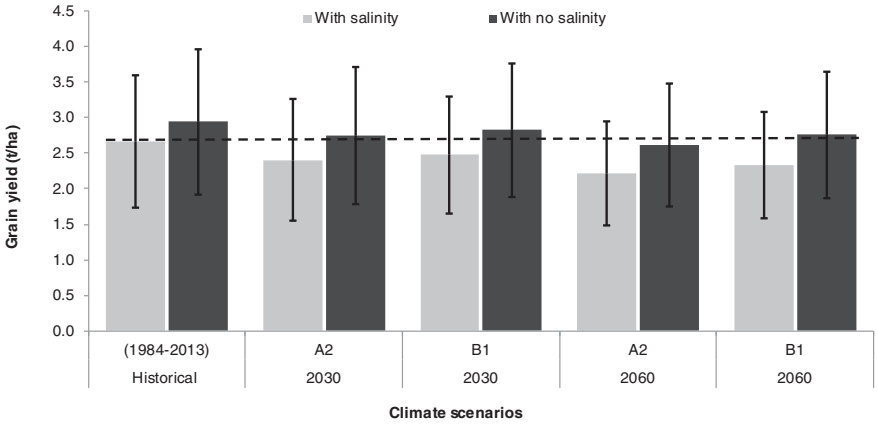

Fig. 11. APSIM simulated yield of sunflower with and without salinity across the five climate scenarios. Note: Error bars show seasonal grain yield variability around the mean (30 years). Dotted line shows difference between historical yields with salinity and other yields with and in absence of salinity.

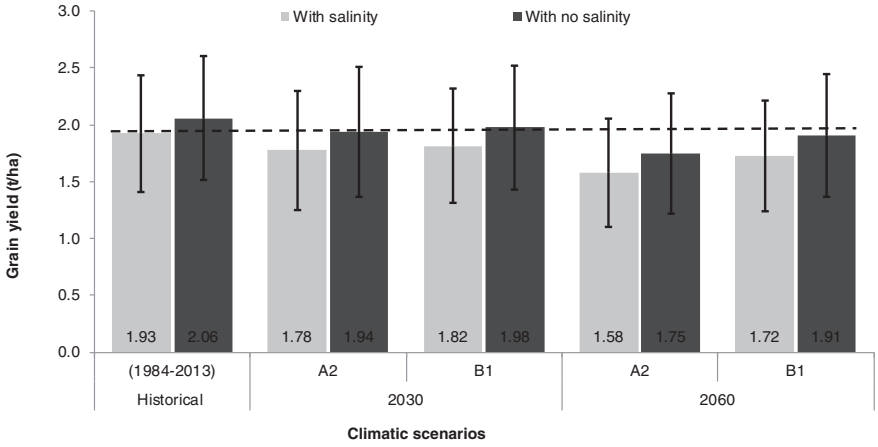

Fig. 12. APSIM simulated yield of salt-tolerant wheat with and without salinity across the five climate scenarios. Note: Error bars show seasonal grain yield variability around the mean (30 years). Dotted line shows difference between historical yields with salinity and other yields with and in absence of salinity.

Table 7
Farmers' estimated historical and extrapolated performance of watermelon and pumpkin across four future climate scenarios.

Climate scenarios	Yield (t/ha)	
	Watermelon	Pumpkin
Historical	29.6	18.8
2030 A	25.2	15.1
2030 B	26.0	15.6
2060 A	17.6	13.7
2060 B	19.5	12.9

generally decreasing trend for maize yields in tropical regions, though their review also indicated several studies which suggested increased maize yields, similar to the results reported here. Moreover, maize yield has been reported to increase by 9–15% in a CO_2-enriched atmosphere as water use efficiency (WUE) of maize dramatically increases (Xiong et al., 2007). The APSIM-Maize parameterisation and calibration for this study used the latest data from the AgMIP project for maize (Bassu et al., 2014), local climate data, and local farm management rules, giving us confidence in the predictions. Nelson et al. (2010) projected that yield loss in irrigated wheat in South Asia would be 38–48% by 2050. However, this finding is general to South Asia whereas the APSIM results reported here are specific to Bangladesh and generated with a salt-tolerant wheat variety. Hence we consider our results to be plausible.

Overall, while the results from the APSIM model used in this study are somewhat more optimistic, they are broadly consistent with the studies cited above and are considered to be acceptable, given the advantage of being specific to the region under consideration. Local soil properties and farmers' management practices were used in the APSIM model, informed from the AgMIP Project (Rosenzweig et al., 2013). Moreover, the impacts of climate change and salinity were projected for crops grown within specified cropping systems, while most previous studies project impacts on individual crops in isolation. However, the APSIM simulations do not make any assumptions about changes to irrigation water availability due to future climate change – water is assumed to be non-limiting.

In contrast to direct climate change impacts discussed above, yield loss due to salinity was projected to be significant for DS rice (52–68%), EWS rice (43–45%) and maize (27–45%) across all climate scenarios in the face of increased variability of rainfall. Sunflower (10–18% loss) and salt-tolerant wheat (9–11% loss) were relatively less sensitive to salinity. The ability of APSIM to model the impacts of crop salinity is novel and arguably the validation base could be broader to enable extrapolation to other salinity-affected rice environments (e.g., Mekong delta). For instance, soil salinity varies considerably between locations, yet in this study we were only able to model salinity for one location (albeit representative of large areas of coastal Bangladesh). In future, as further model enhancements are undertaken, our confidence in the salinity responses will grow. However, we are confident that we are capturing the general trends correctly. The losses reported here are much more pronounced than the adverse impacts of climate change per

se and are cause for concern. In the short term, it is likely that choice of more salt-tolerant crop varieties and changes of planting times will be able to offset incremental increases in salinity. However, in the long term, increasing salinity may make cropping unviable, requiring a more transformational change to the farming system, e.g., to aquaculture-based systems. These trends can already be observed in south-west Bangladesh in places where salinity levels are already higher, e.g. > 6 dS/m (MoEF, 2009; SRDI, 2012; WB, 2013; IPCC, 2014a). A more detailed discussion of response options is provided in a companion paper (Kabir et al., 2018).

As in any modelling study using projected climate data, there is a degree of uncertainty in the results – due to uncertainty in the climate projections themselves, uncertainty in the salinity projections, and a degree of uncertainty in the behaviour of the model. Additionally, APSIM does not consider weeds, pests, and diseases, or extreme weather events such as cyclones and floods, and an assumption was made that irrigation water was not limiting under future conditions. Additionally, future climate may exhibit increased seasonal variability, which was not considered in this analysis. All these uncertainties could compound or offset each other, but a full uncertainty analysis is beyond the scope of this study. Perhaps the greatest uncertainty in our present ability to model climate change impacts is the inability to include projections of extreme events. In the context of coastal Bangladesh, such extreme events are likely to increase the incidence of flooding (Timsina et al., 2016), which is not captured in any of the studies to date. Thus, while unit area productivity might not decline much for many crops, aggregate production levels of rice are likely to be affected as the extent of crops damaged by flooding and sea water intrusion increases.

It was more difficult to extrapolate the impact of climate change and salinity on DS fruit and vegetable crops and aquaculture, due to the lack of published studies and our inability to simulate likely outcomes. However, secondary data and expert opinion suggested that watermelon and pumpkin are likely to be severely affected, with watermelon yield decreasing by 12–15% by 2030 and a further 25–30% to 2060, while pumpkin yield would decrease by 7–10% in 2030 and a further 12–15% in 2060. Yields of fish and shrimp are expected to be not greatly affected. We suggest that further studies are warranted to confirm and better understand the results of our investigations, and these may require the use of appropriate models or controlled environment experimentation.

5. Conclusion

Climate change is projected to have both positive and negative impacts on crop yields in Dacope Sub-District, Khulna, but increasing salinity is always projected to impact negatively on crop responses. The loss of crop production was negligible under projected 2030 conditions (including both climate and salinity changes), even under farmers' current practices. Under 2060 conditions, the adverse impacts on WS rice, DS irrigated rice, and wheat remained negligible, while sunflower experienced notable yield decline. However, the effect of 2060 conditions on rainfed EWS rice and irrigated DS maize was positive. Our study did not consider potential changes to fresh water availability for irrigation. The key insight is that (allowing for the uncertainties discussed earlier) climate change in itself does not pose a major risk to crop production and aquaculture in south-west coastal Bangladesh over the next 15–45 years. However, projected 2060 climate conditions pose risks for some crops, and increasing salinity is an unambiguously negative influence across the five scenarios analysed. Findings of this paper could be applied to the extensive saline and non-saline coastal areas and deltas of South Asia (or even beyond) where similar environments prevail and form a basis for policy interventions related to climate adaptation.

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